講演番号 046 文献番号 20195046

*x*EV Thermal system control

- solving the multi-variable constrained control challenge -

Peter Fussey 1)2) **Cedric Rouaud** 1) **Peter Martin** 1)

1) Ricardo UK, Shoreham Technical Centre, Brighton, BN43 5FG, UK (E-mail: peter.fussey@ricardo.com)
2) University of Sussex, Falmer, Brighton UK.

ABSTRACT: The increasing electrification of vehicle powertrains has resulted in complex thermal systems. The performance of the thermal system has a strong impact on the electric range. This paper will discuss different thermal system concepts and the related control strategies to optimise their performance. The control algorithm complexity has increased with multi-variable systems and temperature limits that result in a challenging control problem. This paper will discuss the use of model predictive control and optimal control approaches to develop the control solution for this problem. These techniques have the additional benefit of reducing calibration effort whilst delivering efficiency gains.

KEY WORDS: **Optimal Control, MPC, Thermal System**

1. INTRODUCTION

The global drive to reduce CO_2 emissions has accelerated in recent years following the Paris agreement, [1]. This has led to the introduction of many national government targets to increase the electrification and eventual banning of petrol and diesel passenger vehicles, for example the EU 2050 long term strategy for reducing green house emissions [2].

Vehicle manufacturers are introducing ranges of electrified vehicles with a multitude of system architectures. Hybrid Electric Vehicles (HEV) range from *mild* hybrids with some regenerative braking through to *full* hybrids with fully electric (EV) operation. The battery systems for full hybrids can be enlarged and combined with charging interfaces to give a Plug in HEV (PHEV). Vehicles without combustion engines are often referred to as Battery Electric Vehicles (BEV) and these can be enhanced with a small combustion engine to give a Range Extended Electric Vehicle (REEV). This family of architectures is often refered to as *x*EV vehicles, where *x* can be *H, PH, B, RE* and so on.

This paper considers the impact of these architectures on the design and control of the thermal system and is structured as follows; Section 2 introduces thermal system architectures, Section 3 formulates the thermal system control problem, Section 4 applies Optimal control theory to the thermal system control and Section 5 discusses the extension to Model Predictive Control.

2. THERMAL SYSTEM ARCHITECTURE

2.1. *x*EV thermal system objectives

All *x*EVs have complex powertrain architectures including batteries, inverters and electric motors, with or without a combustion engine. These systems all have different thermal requirements that need to be serviced by the thermal system that also manages the cabin temperature.

Lithium-ion based batteries have an optimum operating temperature typically around 35˚C. At lower temperatures the power available to the powertrain is limited by chemistry and the resistive losses increase, whilst at higher temperatures the power is limited to protect the cells from damage.

Inverters and electric motors have upper temperature limits, above which they will suffer damage, however their electrical performance is not strongly affected by lower temperatures. Though as with all the powertrain, friction increases at lower temperatures.

The target cabin temperature is set by the driver and passengers. Humans are sensitive to temperature fluctuations, [3], and a range of +/- 1˚C should be targeted once the vehicle is warmed up. These objectives are summarized in Figure 1.

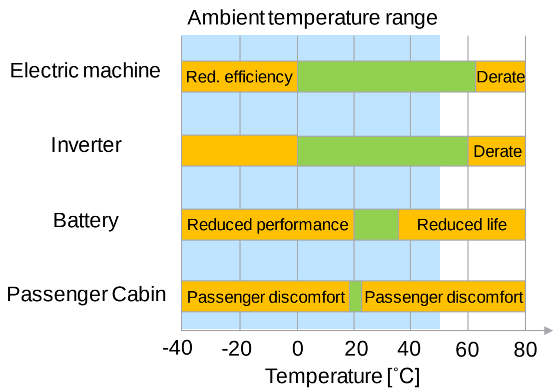

Figure 1: Thermal system objectives

2.2. *x*EV thermal system use cases

The thermal system objectives are to be achieved over many use cases that cover *x*EV operation. This paper will consider a dry operation of the thermal system, i.e. without demist or defogging which is an additional use case.

From the control system point of view, the use cases can be grouped into two main modes of operation; warm up / cool down to operational temperature and disturbance rejection once at operational temperature.

2.2.1. Transient to operational temperature

The challenge when the driver starts the vehicle is to achieve operational temperature as quickly as possible and using as little energy as possible. During this phase there are tradeoffs to be made between the performance of the different components in the vehicle and the driver comfort.

2.2.2. Disturbance rejection at operational temperature

Once at operating temperature, the vehicle is subjected to rapid disturbances in the form of fluctuating tractive power demands and slow variations in ambient conditions. This paper will consider the rapid disturbances as the slower variations are less challenging to the control system performance.

2.3. *x*EV thermal system architectures

The thermal system objectives and use cases feed into the design of thermal system architectures. With the different thermal requirements for different systems, system architectures are being developed with multiple cooling circuits. The requirement for efficient heating has motivated the increasing use of heat pumps in conjuction with direct electrical heating with Positive Temperature Coefficient (PTC) heaters.

This paper will use the example of a BEV to illustrate the control system developments. In this example, the BEV has two coolant circuits; one for the cabin (yellow) and one for the battery

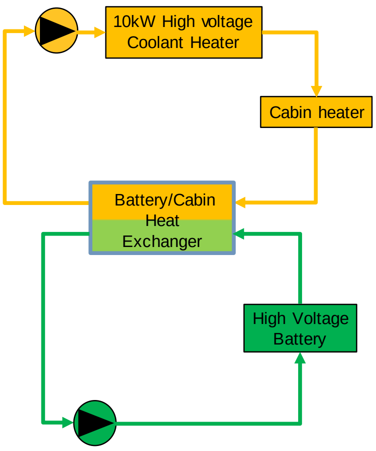

Figure 2: BEV thermal system during warm-up

(green). They both have pumps and are joined with a heat exchanger. In addition, this paper will only consider the warm-up use case which simplifies the thermal system as follows; the radiators are by-passed and the air-conditioning circuit is not required during this mode as shown in Figure 2.

3. CONTROL PROBLEM

A first step in developing the control approach for an *x*EV thermal is to reduce the complex thermal system architecture to a standard control problem to allow the control designer to take advantage of standard control design techniques.

3.1. *x*EV thermal system in a control context

Control problems are defined in terms of the following quantities: control inputs, disturbances, outputs, states and set-points or objectives. The control inputs to the system come from the controller and are typically actuator settings. Disturbances are also inputs to the system, but are independent to the controller and may include changes in ambient conditions for example. The states of a system can be defined as the minimum number of quantities that define the system response at a given time and depend on the inputs, states and disturbances, the states may include temperatures and state of charge of a battery. The output variables are a function of the states and are typically sensor signals such as thermistor signals.

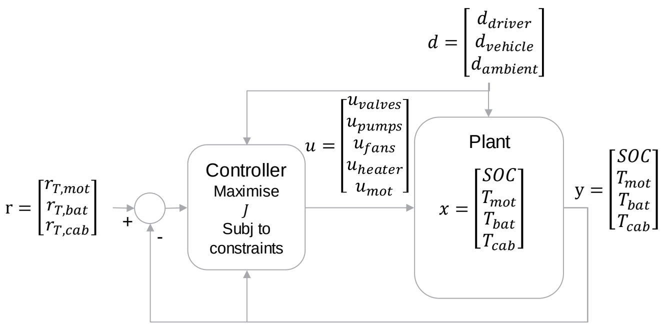

Figure 3: Control representation of a BEV thermal system

An example of the control representation is given in Figure 3 where *r* are reference or set-points, *u* are controller outputs, *x* are states, *y* are system outputs and *d* are disturbances.

3.2. Use case 1: Warm-up

Warming an *x*EV up from cold can require significant energy consumption and therefore have a large impact on the electric range of the vehicle. Traditional control design targets the operational temperatures without consideration of the impacts on energy consumption. With the thermal system in Figure 2, the controller can achieve the target temperatures through different paths. For example, the PTC heater is used to heat the coolant and then the coolant used to heat the cabin and battery. The controller then needs to decide where to direct this heat, to the battery or to the cabin or both. The traditional control design may have two feedback loops, one for the cabin and one for the battery. They will both try to heat up as quickly as possible with the relative speed to achieve set-point being a function of the calibration of the gains. They will also not take the overall energy requirement into account.

In this paper, rather than relying on calibration of gains, a control structure is investigated to allow the automatic trade-off of control values. The calibration can be designed to prioritise responses of one system over another whilst also taking overall energy consumption into account.

3.3. Use case 2: Vehicle at target temperature

Once the vehicle and powertrain are at target temperatures, the controller operates in disturbance rejection mode. Traditional controllers can include feed-forward control of disturbances such as the driver power demand, and observers to allow the control of critical system temperatures that may not have a direct measurement.

Challenges for this use case include regulation of the temperature within limits whilst minimizing the energy consumption. Optimal control strategies can simultaneously include constraints whilst minimizing a user defined function, known as an objective function.

3.4. Objective function selection

An objective function *J* can be introduced that is minimized by the controller. The selection and calibration of *J* allows the system response to be tuned to meet the overall vehicle objectives. The objective function is integrated over a finite horizon and has weights, w_i, for prioritizing one objective over another.

$$J(t) = \int_{t_0}^{t_f} \{P_{PTC} + w_1 T_{error_{cab}} + w_2 T_{error_{batt}}\}\, dt$$

where P_{PTC} is the heater power and T_{error} is the temperature error from set-point.

The thermal system is also subject to constraints such as a maximum heater power, maximum heat transfer rates from the coolant to the cabin and battery and temperature limits for all three systems.

The addition of contsraints to the optimization of the objective function increases the complexity of the problem. Methods to solve these problems include:

- Optimal Control – that is typically solved off-line over the time period of interest. Within optimal control solvers, there are many different approaches and formulations, [4].
- Model Predictive Control (MPC) – that solves an approximation to the optimal control problem over a finite time horizon that can be implemented as a causal controller. Benefits of MPC include the treatment of multiple inputs and outputs and constraints.

4. OPTIMAL CONTROL

Optimal control problems are of the form: for a non-linear system defined by $\dot{\boldsymbol{x}} = f(\boldsymbol{x}(t), \boldsymbol{u}(t))$, find the admissible control function $\dot{\boldsymbol{u}}^*$(t) which cause the system to follow admissible state and output trajectories, $\dot{\boldsymbol{x}}^*$(t) and $\dot{\boldsymbol{y}}^*$(t) respectively. Where the asterisk denotes the extremal or optimal quantities and admissible means within constraints.

From standard texts of optimal control, for example [4], the first order necessary conditions for optimality are given by the Pontryagin minimum principle:

$$u^* = \arg\min_u H\,(x, \lambda, u, t)$$

Where *H* is the Hamiltonian function: $H(x, \lambda, u, t) = \lambda^T f$ and λ is the costate vector. (Note: this the Mayer form that is equivalent to the Bolza formulation with an objective function.) Using this notation, the state and costate dynamics are given by; $\dot{x} = \nabla_\lambda H$ and $\dot{\lambda} = -\nabla_x H$. These two equations form a two point boundary value problem in which the initial state and costate are specified. For admissible $\boldsymbol{u}$, this implies the strong form of the minimum principle:

$$\nabla_u H = 0$$

The optimal control problem can be solved using either direct or indirect methods. Direct methods discretise the original problem and translate it into a non-linear programming problem, while indirect methods solve numerically the first-order necessary conditions described above.

In this section, a direct pseudo-spectral numerical method based on the Legendre-Gauss Radau collocation has been applied to the optimization of the thermal control problem using a generalized solver, *GPOPS-II*, [5]. *GPOPS-II* has been shown to be capable of addressing complex control problems using fast, robust solvers. This involves discretizing the state and control vectors and draws on the established relationship between the Karush-Kuhn-Tucker optimality conditions for non-linear programs and the first order conditions for optimal control.

4.1. Optimal control model

The starting point for the optimal control analysis is a system model that includes the responses and interactions that need to be controlled and optimized. The BEV thermal system from Figure 2 has been modelled with lumped masses and heat flows as shown in Figure 4, resulting in four thermal states.

Taking these in turn, the cabin coolant circuit (yellow) has heat transfer in from the motor and PTC heater and heat out to ambient, battery cooling circuit via a heat exchanger (HX) and the cabin, via a blower fan. The battery cooling circuit has heat transfer in from the cabin cooling circuit and heat out to ambient and the battery, using C_x = heat capacity for system x.

$$C_{ccool}\dot{T}_{ccool} = P_{PTC} + P_{mot} - P_{cab} - P_{ccool2amb} - P_{HX}$$
$$C_{bcool}\dot{T}_{bcool} = P_{HX} - P_{bcool2amb} - P_{batt}$$

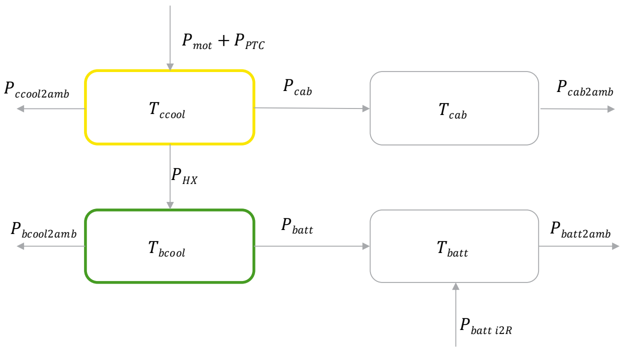

Figure 4: Lumped mass thermal model

For the two systems under temperature control; the cabin has heat in from the blower and out to ambient, whilst the battery has heat in from the coolant and out to ambient but also has the resistive heating from the battery itself.

$$C_{cab}\dot{T}_{cab} = P_{cab} - P_{cab2amb}$$
$$C_{batt}\dot{T}_{batt} = P_{batt} + P_{batt\ i2R} - P_{batt2amb}$$

The lumped thermal masses are coupled to the electrical system through the PTC and electric drive currents. The resistive losses in the electric drive are fed back to the thermal circuit as powers from the battery, $P_{batt\ i2R}$, and motor, P_{mot}. A fifth state is introduced for the stored energy in the battery or the state of charge. The stored energy is reduced by the combined power to drive the vehicle and provide the additional heating through the PTC heater.

The controller was given three control signals to vary, the PTC power, the blower speed and the heat transfer between the the two coolant circuits – a function of the pump speeds in the actual vehicle.

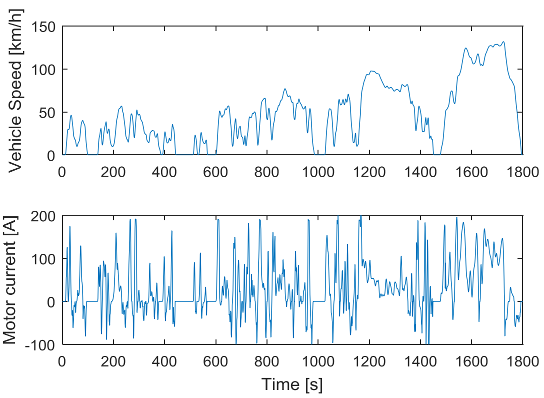

Figure 5: WLTP drive cycle

The vehicle is driven over the WLTP cycle that defines the power required at the wheels, Figure 5. This power is drawn from the battery and the resulting current is used to calculate the resistive heating in the battery. The internal resistance of the battery is implemented as a function of temperature and reduces with increased temperature.

In addition, the model parameters were updated to allow the control performance to be studied over the WLTP cycle. Due to the large thermal inertias in the original system, the simulation would take longer than the WLTP to stabilise temperatures. For this reason, the thermal masses were reduced artificially and secondly, the initial temperatures were not set too low.

4.2. Preparation for application of optimal control

The solution of the optimal control problem requires that the model is continuous and differentiable. In addition, the model should be scaled to improve the conditioning of the optimization and finally care was taken to avoid singular control problems.

Having already adopted a lumped mass modelling approach, the only updates were to replace look up tables with a polynomial approximation.

The scaling used in this simulation was applied at the initial problem setup, using scaling factors based on the key dimensions; [mass], [length], [time], [amps], [temperature]. From which the other scalings can be derived, for example:

[power] = [mass]x[length]^2/[time]^3

During the model configuration, care was taken to avoid singular control situations. This means cases where a controller has no impact on the objective function or constraints and can therefore take any value. For example, if two lumped masses such as the cabin coolant and the cabin, are at the same temperature, then the blower can vary from 0 to 100% with the same heat flow (zero flow). This was addressed by penalizing all the control signals so the optimisation prioritized control actions that gave a significant improvement in objective function.

4.3. Investigation of potential objective functions

Once the optimal control structure is in place, it can be used to investigate potential objective functions. The analysis started with a cost function that minimized the energy drawn from the battery. With constraints introduced to address the temperature control. In this example, the optimization is set up to achieve the target temperature at the end of the WLTP, whilst minimising the total heat loss from the battery.

The optimization has been run with initial temperatures of 20˚C and 15˚C, in Figure 6 and Figure 7 respectively. The resulting optimization has several features;

- The battery has a larger inertia than the cabin so heating has to start earlier in the cycle to reach the target temperature.
- The cabin is only heated up at the end of the cycle since the power is being minimized and if it is heated up earlier, more

heat would be lost to the ambient. This illustrates the optimisation working, however would be updated to maximise driver comfort in a vehicle application.

- The PTC heater power is phased in time with the drive current to/from the motor. This is to minimize the resistive heating losses that are a function of the current squared, so there are less overall losses if the PTC heater is used when the motor is at a low power.

From these results it is possible to envisage a rule based control strategy that has a threshold for the heater power based on the drive current and temperature error.

The objective function was subsequently updated to minimize both the PTC heater energy and the error in the battery temperature from the reference value, as introduced in Section 3.4. The results are presented in Figure 8 and show that the optimisation increases the PTC heater power until the battery reaches the target temperature. Thereafter, the PTC heater is used to maintain the temperature. Amount that the PTC heater is increased is controlled by the relative weightings between the separate components in the objective function. The results from this illustrative example show the electrical power losses are approximately 8% higher when the weighting is increased to improve the thermal response of the battery.

Finally, the optimisation of the electrical power suggests that the impact of the temperature on the internal resistance appears to be a second order effect because the controller does not try to raise the battery temperature quickly, to reduce the internal resistance, but rather phases the heater power with the motor demand.

5. MODEL PREDICTIVE CONTROL (MPC)

The optimal control study is solved offline and can be used to guide the development of an online controller, either updating a conventional rule based controller or by providing the starting point for MPC.

An MPC solves an approximation of the optimisation of the cost function in real time. With relatively slow dynamics, the thermal system is well suited to the application of predictive control as the optimisation can be carried out within the controller update time step.

The optimal control problem from Section 4 provides a good starting point for MPC with an efficient control orientated model and an objective function structure. The use case is also well suited to MPC since it covers a time scale that is similar to the dynamic response of the thermal system.

Updates to the control approach for MPC include:

- It may be possible to simplify the model further, removing second order features such as the variation of battery resistance with temperature.
- The inclusion of the drive power should be considered as a feed forward input since it is difficult to predict over the horizon, allowing the PTC heater can respond to the signal at the lower level.
- Integration with a route planner to predict future drive power demands. This case also requires consideration of how to handle the shortening horizon at the end of the trip.

6. CONCLUSIONS

The solution of optimal control problems using the pseudo-spectral collocation method is a powerful technique to explore the control problem itself, allowing the control development engineer to understand the system under control and try different control structures, for example different cost functions and limits.

The optimal control study provides a powerful framework from which to explore different options for subsequent implementation into Model Predictive Controllers.

Future work will include the extension to use case 2 – disturbance rejection, the implementation of a model predictive controller for BEV thermal system control and extension to more complex thermal systems, for example with the inclusion of heat pumps.

In addition, the optimization approach will be extended to optimize the system and the financial cost of the overall solution (hardware and advanced thermal control): it will use the exergo-economy approach. Exergy-based analysis helps to understand where inefficiencies are in the system, calculating exergy destruction and exergy losses. It will also estimate the cost of production of the systems products (e.g. electricity, brake power) through cost allocation techniques.

7. ACKNOWLEDGEMENTS

The authors acknowledge the support of Ricardo and the University of Sussex.

REFERENCES

[1] https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement accessed 1 April 2019.

[2] http://ec.europa.eu/clima/policies/strategies/2050/ accessed 1 April 2019.

[3] T Han and L Huang, A Sensitivity Study of Occupant Thermal Comfort in a Cabin Using Virtual Thermal Comfort Engineering, SAE 2005-01-1509.

[4] D E Kirk. Optimal Control Theory: An Introduction. Dover Publications, 2004.

[5] M A Patterson and A V Rao. GPOPS-II. a general-purpose matlab software for solving multiple-phase optimal control problems. University of Florida, May 2014.

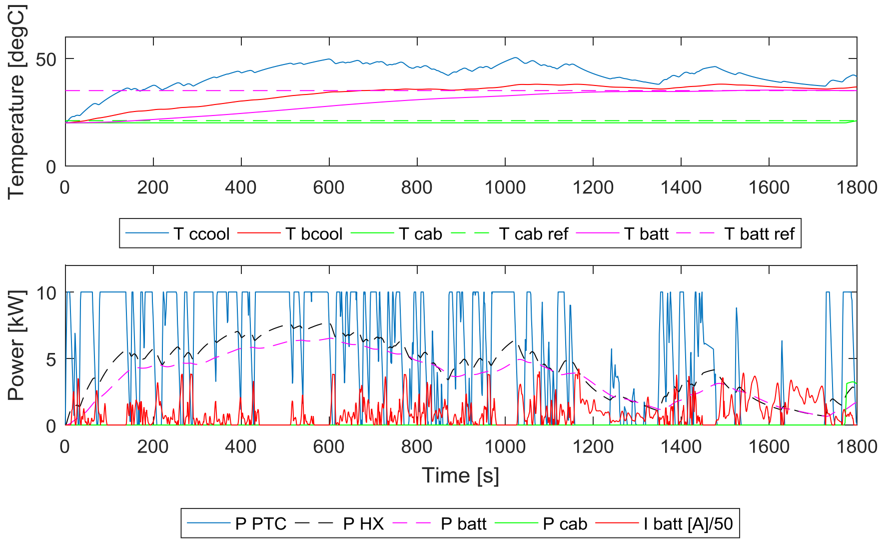

Figure 6: Optimisation results for WLTP starting at 20˚C

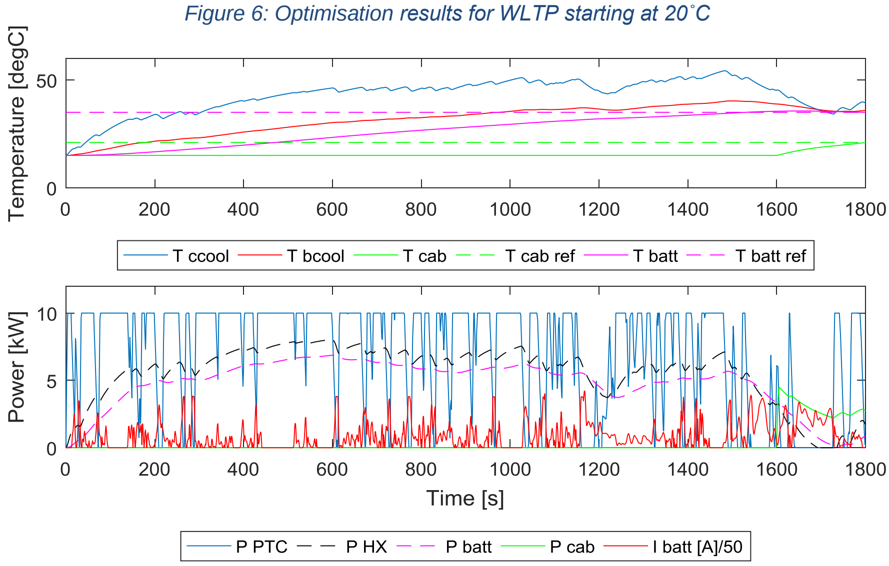

Figure 7:Optimisation results for WLTP starting at 15˚C showing increased PTC heating

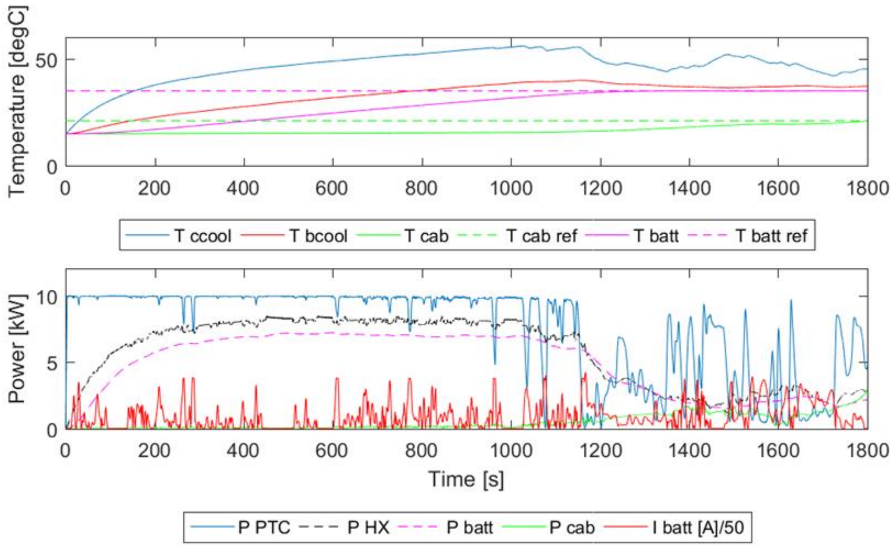

Figure 8: Optimisation results for WLTP starting at 15˚C with tradeoff between energy and temperature error showing the reduced battery temperature error